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Examining Pareto Law across department store shoppers

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Examining Pareto Law across Department Store Shoppers

Abstract

Department stores invest in loyalty strategies that largely focus on retaining current high value customers in response to increasing competition in retail shopping. In this study, we examine the contribution of the top 20% customers for transaction frequency and value ("heavy buyers") to the total sales, and the consistency of this contribution across departments within a store. We also investigate the heavy buyer stability over time across three years, from over 550 million transactions from a department store chain in East Asia. The results show that the Pareto ratio of the top 20% spenders account for 71% of revenue (and 52% of the total transactions), and the top 20% transactors represent 58% of revenue (and 62% of total transactions), which may signal the role of such heavy buyers to overall stores sales. At each department level, the heavy buyers (by value) contribute from 65% to 86% of the department revenue. Despite this, the stability of the top 20% segment over time varies greatly by department from 11% to 74%. Finally, whether high value customers in one department store also translate across departments, depends mainly on the department size in terms of its shopper penetration. The research furthers our knowledge on Pareto Law, with important implications for customer retention strategies and loyalty programs especially for retailers.

Key words: Consumer loyalty, heavy buyers, Pareto Law, retailing, stability

1 Introduction

Department stores face competition from online and mobile distribution channels in an omni-channel retailing world (Verhoef, Kannan, & Inman, 2015). Facing these competitive pressures, it seems reasonable for department stores to focus their attention and limited resources on retaining their valuable customers, specifically those who currently contribute the most to the company's bottom line (also known as *'heavy'* customers). 'Heavy' is a term that is often used by marketers to refer to customers who buy more than other customers (Twedt, 1964). In line with Recency, Frequency and Monetary value (RFM) targeting models, heavy customers are more desirable targets for marketing activities than their lighter counterparts (e.g., Fader, Hardie, & Lee, 2005). This approach aligns with around 80% of brand managers believing that loyalty programs are more profitable when targeting heavy rather than light customers (Wansink & Park, 2000). This belief would subsequently influence how brand managers direct their marketing investment and valuable resources.

One common classification of heavy customers is via the Pareto share (or also known as Pareto ratio), which refers to the sales/revenue that can be attributed to the top 20% of a brands' customers (Anschuetz, 1997; Dubinsky & Hansen, 1982; Kim, Singh, & Winer, 2017; McCarthy & Winer, 2019; Schmittlein, Cooper, & Morrison, 1993). McCarthy and Winer (2019) extended Pareto share analysis settings outside of consumer packaged goods' (CPG) markets and found the average contribution of the top 20% to be 67% overall. Their study included separate retail categories such as clothing and clothing accessories, general merchandise, as well as food services and drinking places. This research further extends analysis into Pareto share within a non-CPG setting, specifically into a department store environment, where a department store is split into various departments selling very different products from food to fashion to furniture. This means department store managers need to manage both overall revenue and foot traffic, as well as the performance within each department where products, interpurchase frequency, value, and level of customer service can vary considerably. The research contributes to the knowledge on how heavy buyers contribute to the total department store revenue and within each department. Furthermore, it will also help department store retailers appropriately allocate resources, such as staffing levels and promotional activities, across departments.

This research also utilises a store's loyalty program data. Loyalty programs have been an area of considerable investment by retailers. This paper details an additional approach to analysis of the vast amount of data retail organizations collect though their loyalty cards, to improve the informational value of the data generated by loyalty programs (Breugelmans et al., 2015; Chaudhuri, Voorhees, & Beck, 2019). The data covers over three years of purchases from a high-end department store retailer in East Asia, containing more than 553 million transactions across over 30 stores and twelve within-store departments.

This study continues the conversation on the extent of the contribution of heavy buyers for the business, and how the stability of the contribution over time. Although the context of the research is within a department store setting, the findings are highly relevant for academia and industry practitioners beyond this environment – especially with the challenge on resource allocation across heavy and light buyers.

2 Background

2.1 The Pareto share as a way to quantify the value of heavy customers

The Pareto share is the contribution of the top 20% of a brands' customers in a specific time period. It can vary from 20% (if all customers make equal contribution) to 99.99% if the top 20% account for almost all of a brand's sales.

Historically, CPG categories dominate the research on heavy buyer contribution *(see Table 1)*, as the analysis requires individual level data over time. This is easily accessible via household buying panels as managed by Nielsen, Kantar and GfK. Previous studies have found that the top 20% of buyers annually contribute around 50% of a brand's total yearly revenue (e.g., Anschuetz, 1997; Twedt, 1964). As the time period for the CPG calculation increases, so does the Pareto share – as a longer time frame gives more opportunity for lighter brand buyers to be included, thereby making the top 20% looks heavier. For example, Kim et al (2017), over a time period of six years, report an average Pareto Share of 73%, close to the 80% commonly cited (Koch, 1999).

[INSERT TABLE 1 HERE]

Most of the studies were conducted with end consumer contribution being the focal measurement, with two notable exceptions: the study by Bennett (2016) examines airplane purchases by airlines (with the Pareto share of 56%), while Martin et al. (2020) focuses on the unit sales and revenue contribution of the top 20% transactions across different types of retailers (the contribution being 50% of the unit sales and 38% of the revenue). Pareto share has also been used as a measure of manufacturer concentration across product categories (as per Tanusondjaja, Dunn, & Miari, 2020) – with the top 20% of manufacturers covering 90% of the total revenue across 16 product categories.

In studies that have covered non-CPG companies, the average Pareto share is 52%. McCarthy and Winer (2019) find the overall average Pareto share of 67% for non-CPG companies in general and 66% for services firms, drawing on data over a two-year period. However, modelling revealed different aspects of the retail sector have significantly lower than average Pareto shares. Therefore, it is important to check the Pareto shares for different departments within a department store, as these Pareto shares could differ substantially, affecting strategy and resource allocation.

2.2 *Temporal Stability of Heavy Buyers*

Before targeting a specific type of buyers, it is necessary to be able to accurately identify them. Drawing on a stable characteristic is preferable as this allows better attribution of changes to marketing interventions (Wright, 1996). If the classification characteristic lacks stability (e.g., attitudes or personal interests), there is a risk that the buyer characteristic could change between classifications and when the person is reached through targeted marketing efforts.

Despite the common use of demographic and other personal information to target buyers, extensive research on demographic profiles of buying frequency segments has been unable to meaningfully distinguish heavy buyers from others using information such as gender, age, and income – as well as other variables that include geographic locations, personality, and socio-economics (Frank, Massy, & Boyd, 1967; Goldsmith & d'Hauteville, 1998; Twedt, 1964; Wansink & Park, 2000). With the readily available buying behaviour data (e.g., loyalty card usage), managers are now able to directly target heavy, light, or non-buyers based on past behaviour for marketing interventions. This leads to the question on the stability of this approach, particularly amongst heavy buyers who are most valuable customers for retailers. Ideally, any changes in behaviour across such customers can be attributed to the marketing intervention. Romaniuk and Wight (2015) found year-on-year heavy buyer stability in CPG categories to average 67% at category level and 50% at brand level, with more variation between categories than between brands within a category. These authors discuss three external factors as drivers of brand buying stability: changes in household factors (size and income); changes in brand preferences due to new launches and advertising; and statistical considerations such as classification error and regression to the mean. These factors could also affect the stability of the department store buyer' buying frequency.

Another important consideration is assortment heterogeneity: department stores have heterogeneity in product range and prices across departments, which can range from furniture pieces costing thousands of dollars to food items under $10. The wide assortments provide shoppers with a wide choice of products and services to fulfill their needs, and to reduce the possibility of them visiting other competing chains (Beatty, Mayer, Coleman, Reynolds, & Lee, 1996; Donelly, Gee, & Silva, 2020; Thang & Tan, 2003). As foot traffic is important in this environment, department stores also provide services such as in-store dining to attract a wider customer base and to provide a reason to visit, along with the wide assortments of product ranges (Kim, 2001).

The variety of products and services within a department store has an impact on visiting frequency and spend within a specific department: some departments have the potential to be visited regularly and others, more rarely. This also means wide variation in the contribution of each department to the overall department store sales. These differences also provide a different context to examine whether we would see any evidence of Double Jeopardy pattern for department store purchases, in terms of each department's penetration and purchase frequency and how they relate to the revenue contribution to the whole department store. Double Jeopardy shows that bigger brands are rewarded twice by having more buyers who buy slightly more frequently (Ehrenberg, Goodhardt, & Barwise, 1990; McPhee, 1963).

As marketing interventions can also focus on transaction frequency and not the sales amount, we also examine the Pareto share for transaction frequency. This is important, as the Pareto share for transaction value could be skewed by few people with particularly large purchases, who might be unlikely to repeat their purchases in the next year (e.g., large purchases of home décor, or a major purchase of sports equipment in a particular year).

Therefore, in addition to examining stability of heavy buyers within a department, we investigate whether heavy customers in one department are more or less likely to be heavy customers in another department, e.g., whether heavy buyers in home décor are more or less likely to spend more heavily in apparel. We conduct this investigation by applying the cross-purchasing analysis, which quantifies the percent of buyers who purchased one brand who also purchased another brand within a particular category. The generalized pattern within such analysis has been described as the *Duplication of Purchase Law.* Duplication of Purchase Law states that brands share customers in line with competitor penetration. This provides a benchmark for the probability of a second brand being purchased if the condition of the first brand being purchased is met (Ehrenberg, Uncles, & Goodhardt, 2004). This law has widespread applicability ranging from media channel usage, supermarket choice, to category co-purchases in supermarkets (e.g., Keng & Ehrenberg, 1984; Lees & Wright, 2013; Tanusondjaja, Nenycz-Thiel, & Kennedy, 2016; Anesbury, Jürkenbeck, Bogomolov, & Bogomolova, 2021). We use the same analysis to investigate whether one department's heavy buyers are also heavy buyers of another department, and whether such cross-purchasing levels are predictable from the size of the heavy buyer cohort for each department. This has implications for predicting likely customers when in-store department-specific promotions occur.

This leads to the following research questions about the value of heavy customers to the store as a whole and by department:

RQ1: What is the Pareto share in a department store sales context, and is it the same for both transaction value and frequency?

RQ1a: Do different departments within a department store have a similar Pareto share? How similar is the Pareto share within each department across transactions and value?

RQ2: How stable is the contribution of the top 20% for the department store?

RQ2a: How do the heavy buyer stability levels vary for each department?

RQ3: How do departments share their heavy buyers?

3 Method

A prominent department store chain in East Asia[1] provided three years of transactional data (April 2012 to March 2015) from its widely adopted loyalty program. The three-year period was determined by the department store, as the extent of the data shared for the research. The loyalty card program offers several benefits such as annual price discounts, rewards, and complimentary insurance – all of which contribute to high loyalty card usage. Shoppers have to scan their loyalty card to receive exclusive promotions and price discounts, as an incentive to join the loyalty scheme and to take the full benefit of the program. The chain has over 30 stores across the country and carries a wide variety of products from frequently bought food products to less frequently bought apparel, jewellery, furniture, books, home electronics, and home decorative items.

The analysis includes shoppers in the entirety of the loyalty card database and covers 553,335,843 transactions. Each transaction carries information on the purchase value and department in a single shopping trip. With such a large amount of data, statistical testing is of

[1] Information regarding the name of the department store and the exact country location is concealed at the request of the department store chain. The department store also requested for the number of customers not to be divulged as a condition of the data sharing arrangement.

little value, and hence is not reported, in favour of examining managerially significant differences (in line with Kennedy, Scriven, & Nenycz-Thiel, 2014).

The 36 months of data were split into three twelve-month periods, to facilitate further analysis into changes or differences over time. We analysed the total value of the transaction for the department store in total, and then for each department within the store *(see Table 2 for the list)*. This was done to avoid any omission of insights when varying results across departments are masked by the total store figures.

The data for the analysis therefore comprised of the number of transactions (frequency) and the total sales revenue (value) recorded for each customer. While revenue is a key focus, transaction data is also analysed as a close proxy for foot traffic, which is an important retail metric (e.g., Graham, Khan, & Ilyas 2019; Ma & Fildes, 2020; Perdikaki, Kesavan, & Swaminathan, 2012).

4 Results

4.1 Descriptive Results

Descriptive analyses reveal that customers from the department store chain made an average of 44.8 transactions each year (calculated from the total purchases across the period, over the total number of unique transacting customers). At department level, there is considerable variation in both penetration and purchase frequency, ranging from *Food* with 76% of customers shopping at an average purchase frequency of 36.1 transactions per annum, to *Massage* with a penetration of 1%, and a frequency of 1.8 transactions per annum. The Pearson's correlation between department penetration and department purchase frequency is 0.78 ($p < 0.01$). This mirrors the Double Jeopardy pattern found when comparing the penetration and loyalty of brands (Ehrenberg, Goodhardt, & Barwise, 1990; McPhee, 1963) and supermarket shopping (Keng & Ehrenberg, 1984) – which shows that bigger brands are rewarded twice by having more buyers who buy slightly more frequently. Deviations from the Double Jeopardy relationship are also present. The *Beauty* department, with 26% penetration but with a relatively higher 6.2 average transactions per annum, displays the characteristics of a niche 'brand' (Kahn, Kalwani, & Morrison, 1988). Another deviation can also be observed in the *Food* department, with the highest penetration and purchase frequency. Despite only 21pp higher than the next department, it displays the excessive behavioural loyalty characteristics of a dominant 'brand' (Fader & Schmittlein, 1993), with nine times the purchase frequency. However, this Double Jeopardy pattern does not extend to value figures, where the correlation between penetration and value is low and statistically insignificant. This variation supports the approach to compare departments within the store and both transaction frequency and value.

[INSERT TABLE 2 HERE]

Looking at the department revenue contribution, it is also important to note that the penetration of a department is a strong predictor of its revenue contribution to the whole department store ($r=0.95$, $p<0.05$) and stronger than the annual transaction frequency ($r=0.72$, $p<0.05$) and the average transaction value ($r=-0.19$).

4.2 Heavy Buyer Contribution

To calculate the Pareto share for RQ1, customers who bought from a specific department are ranked by annual sales contribution to identify the top 20% for that department. This segment's revenue is then summed and compared to the total department revenue to calculate the top 20% customers contribution. This provides two Pareto shares for each department, one for revenue and one for transactions. The same process is repeated with the annual frequency of transaction used as the unit for ranking.

The results in Table 3 show that for the total department store, the top 20% of heavy buyers by value accounted for 71% of the total value but accounted for only 52% of transactions. Therefore, department store value Pareto share mirrors that found by McCarthy and Winer (2019) in other non-CPG categories or longer run, six-year CPG Pareto share reported by Kim et al. (2017). When the focus is on customers who frequently purchase at the department store, the top 20% of heavy buyers by transaction accounted for 58% of the total value and 62% of transactions. Therefore, in contrast, transaction Pareto share is more in line with other annual transaction Pareto Shares in CPG categories (Sharp, Romaniuk, & Graham, 2019).

Across departments, value Pareto share range is 21 percentage points from a very concentrated 86% for *Traditional costume* to a less concentrated 65% for both *Sports* and *Cleaning* departments (Average = 71%, StDev = +/-6.4). There is a positive correlation between the Pareto share and the average transaction value across departments ($r(11) = .75$, $p < 0.01$), as per Kim et al. (2017) as well as McCarthy and Winer (2019). Unlike prior studies, there is no correlation with frequency of transaction ($r(11) = -.13$, $p = 0.68$). The higher the transaction value, the higher the Pareto share. Therefore, value Pareto share varies by department, and this variation is in line with the average value of spend within the department, but not the frequency of transacting.

When the frequency of transaction is the unit of analysis – for the top 20% customers by value – the variation in Pareto share is higher with the range of 34 percentage points from 70% for *Food items* to 36% for *Men's clothing* (average 52%, StDev = +/- 8.7). There is a positive correlation with average transaction frequency ($r(11) = .66$, $p = 0.01$), and a negative correlation with average transaction value ($r(11) = -.59$, $p = 0.03$). Hence, there is more variation in transaction Pareto share than value Pareto share, and this variation is correlated with average transaction frequency within the department. This suggests within a department store context, value, and transactions are not interchangeable metrics, and the annual Pareto shares of both vary considerably across departments within a store.

These results are in line with the Pareto share of the top 20% customers by transactions. There is lower variation in Pareto share for transaction contribution for these frequent transactors, with the range of 25 percentage points from 77% for *Food items* to 52% for *Gift* (average 62%, StDev = +/- 5.7), and also lower variation in Pareto share for value contribution, with the range of 20 percentage points from 66% for *Beauty products* to 46% for *Décor and Furniture*.

[INSERT TABLE 3 HERE]

4.3 Stability of Heavy Buyers over Time

Benchmarking heavy buyer stability is crucial to detecting the effectiveness of marketing activities to retain or increase heavy buyers. The next analysis examines the stability of high value customers over time, overall and by department – to answer RQ2 and RQ2a. For this calculation, the top 20% heavy buyers each year are tracked over time to the next year, that is, from year-1 to year-2. Mindful that some departments have longer purchase intervals (e.g., *Décor and Furniture*), we also examine stability of high value customers from year-1 to year-3. We examine whether shoppers who purchased a sufficient amount to qualify in the top 20% in one year continue to qualify to be in the top 20% in subsequent year. The results (shown in Table 3) show 69% of shoppers who were in the top 20% of overall department store spenders in year-1, also spent sufficiently to again qualify in the top 20% of department store spenders in year-2, and this figure lowers to 64% when the time frame is extended to two years. This means that while two in three shoppers remain heavy buyers, the remaining one in three initially heavy shoppers churn out of the top 20% year on year for the store overall.

However, at department level, there is considerable variance in annual stability (average 45%, StDev = +/- 18.4). Over one year, the range is 63 percentage points, with the highest *Food items* at 74%, and the lowest *Gifts* at 11%. Across the board, stability declines when the time frame is extended out to two years, averaging 38% but with a similar standard deviation of +/-17.4. The wide differences in stability between the overall department store and across each department highlight the need to have department-focused strategies.

When the focus is on the top 20% of customers with the most transactions, the figures are similar. On average, 48% of these customers will also qualify in the following year (StDev = +/- 17.9), dropping to 40% when the period is extended to two years (StDev = +/- 16.7).

Therefore, there is considerable variation in stability across departments and extending the time frame does not improve the stability, and the instability is not due to insufficient time to capture re-purchase intervals. This highlights the need to create department level benchmarks for stability of heavy buyers over time.

4.4 Heavy Buyer Sharing Across Departments

The final research question (RQ3) examines how the heavy buyers from one department shop across other departments. To answer RQ3, we focus our analysis on the top 20% customers on revenue contribution. The aim is to detect if there are departments that have a high overlap in heavy buyers, which can help plan the timing of department level promotional activities. Rather than attracting sales from the same pool of heavy buyers across multiple departments at the same time, the department store can plan such activities better across the year.

A co-occurrence matrix of heavy customers across the departments is constructed for each year – with the average sharing figures across the departments across three years are reported, as shown in Table 4. We draw on Duplication of Purchase analysis and calculate the proportion of heavy buyers of one department who are also heavy buyers of another department. The cross-purchasing patterns fit the expected Duplication of Purchase Law (Ehrenberg et al., 2004; Goodhardt & Ehrenberg, 1969; Lees & Wright, 2013), with the penetration figures of heavy customers for each department and the cross-purchasing across departments being positively correlated at 0.99 ($p < 0.01$). This means that the high value customers of any department are more likely to also shop at the other more popular departments (in terms of buyers) rather than smaller departments. The Duplication Coefficient *(D)* which is the average of the co-occurrence levels for all departments, divided by the average penetration (Ehrenberg et al., 2004), is 3.0 (year-1), 3.1 (year-2), and 3.1 (year-3). This suggests that there is high likelihood that heavy buyers in one department are also heavy buyers in another department (with the D coefficient being >1.0).

Heavy buyer sharing levels that deviate more than 10pp against the average duplication are highlighted, and these comprise 7% (n=10) of the total instances of potential overlaps. For example, while on average 42% of heavy buyers in any department are also likely to be heavy buyers of *Food items*, heavy buyers of *Books* and *Cleaning products* are even more likely to buy food items, with overlap in heavy buyers of 53% and 65% respectively. There are negative deviations based on distant department locations (*Kids & Baby products* and *Sports products* with *Food items)*. *Cleaning products*' high value customers are also likely to be high value customers of several other departments, suggesting this is an 'add on' purchase often made at the same time as other purchases.

[INSERT TABLE 4 HERE]

5 Conclusion and Discussion

Over 553 million transactions across three years and over different departments for an upmarket department store were analysed for this research. The descriptive results revealed that the metrics for departments within a department store follow the same Double Jeopardy law-like pattern (as per Ehrenberg et al., 1990) seen for competing brands for transaction frequency but not for transaction value. Therefore, increasing department penetration by attracting more shoppers to that department is likely to increase transaction frequency. It is also important to note the strong positive correlation between department penetration and its contribution to the total department store revenue. This suggests that increasing buyer penetration for each department is likely to be positively linked to its share of the total department store revenue, in line with the principles on how to grow brands (Sharp, 2010).

This research also extends prior Double Jeopardy applications to the new context of transactions in 'competing' departments within a department store. This opens the door to future testing in traditionally non-competitive markets, but where buyers must make choices about where to direct their behaviour, such as visiting pages on a website.

The study contributes further evidence that the Pareto share is far more nuanced than the commonly held ratio of 20:80. Within the retail environment, there are factors that would have led marketers to think that the 20:80 ratio would hold. There are high switching costs related to first store loyalty (East, et al., 2000) where shoppers are less likely to venture to a more distant store location. Furthermore, the research utilises a large dataset from loyalty program, that is likely to skew towards more frequent shoppers to the department store. Yet, as reported in this study, the top 20% of buyers by revenue share contributed 71% of the total spend value at the total department store level – a contribution comparable to recent studies exploring Pareto share: 73% by Kim, Singh, & Winer (2017) and 67% by McCarthy and Winer (2019).

Our results also confirm the finding of a high positive correlation between Pareto share and average transaction value to this department store setting. For customers who are frequent transactors at the department store, the top 20% of buyers by transaction share were responsible for 72% of the total transactions but only 56% of the total spend value. Accordingly, alternative tactics will be needed to build spend value, which would include assortment selection and pricing decisions.

The results further add to the knowledge base of Pareto Law research in non-CPG categories. Although some departments in the store cover CPG categories (e.g., *Food items* or *Beauty products*), our research also cover departments with non-CPG categories that have not been explored previously. However, unlike prior research we did not find transaction frequency to be correlated with Pareto share for value. This is most likely because unlike brands within a category, the departments within a department store comprise a wide variety of product types with substantially different prices with no correlation between transaction frequency and transaction value. This highlights that in a department store setting, separate tactics are needed to build transaction frequency and transaction value. This also emphasises the importance of the choice of variable, as well as time frame, for Pareto share analysis and evaluating marketing interventions.

This research also extends past work on the stability of heavy buyers (e.g., Romaniuk & Wight, 2015) previously only conducted in CPG categories to a non-CPG category. The 69% overall annual benchmark for value contribution is similar to category level average higher than found in prior CPG research, the department level results show much more variation at the average of 45%. While this is in line with the 50% stability of heavy buyers at brand level results of Romaniuk and Wight (2015), the across department variation is more in line with their category level variation rather than their brand level variation. This suggests that tactics aimed at retaining heavy buyers are best implemented and assessed at department level rather than overall store level.

We were also able to extend the Duplication of Purchase Law to the specific context of heavy buyers within departments of a department store. To our knowledge, this is the first application of the analysis and law in this context. The findings show a heavy buyer in one department is around eight times more likely to be a heavy buyer in another department. This highlights the risk of cannibalization when one department is conducting events or promotions, sales may come at the expense of other departments. Applying this analysis to the situations when departments run promotions can identify the characteristics of promotional activities that are prone to excess cannibalization, and ones that are not – thereby improving our understanding of retailing behaviour.

Managerial implications

Faced with competition from other brands and alternative channels (e.g., online shopping), department store retailers are struggling in today's retail environment. This research shows a novel use of loyalty card data, where retailers can apply to their own easily accessible data to understand in-store shopping behaviour across departments. The Pareto share for the total store and the Pareto share figures for each department give a guidance for the department store, as to how much resources and efforts would be feasible to retain heavy buyers year on year.

By treating each department as a 'brand' in an in-store competitive market, and applying the Double Jeopardy law-like pattern, retailers can see that for most departments, the key driver of revenue contribution is penetration, or the number of shoppers who bought in that department at least once (in line with Sharp, 2010). The implication of this finding is that growing the number of shoppers for the department is likely to have a positive effect for its revenue contribution to the total store. This analysis can also highlight exceptions to that pattern, such as evident for *Beauty products* for this department store and investigate if the deviation is due to a highly loyal customer base (which can be cultivated further) or a deficit in light buyers (perhaps the design or layout is foreboding for infrequent shoppers).

Looking beyond the Pareto share for the total store also helps to see any localised trends across stores and the varying nature of each store. There are considerable differences in heavy buyer stability for the overall department store with individual departments, such as *Food items* and *Gifts*, thus applying a blanket approach on customer retention across all departments may not produce the desired outcomes. These department level differences in Pareto share can help create a more tailored service strategy based on whether the department is revenue or transaction dominant. Potential customer retention strategies can be tailored depending on the level of heavy buyer stability and whether inducements should be focused on transaction frequency or purchase value. For example, whilst the top 20% of heavy buyers by value in *Food* department contributed 69% of the revenue, these heavy buyers were likely to shop very frequently (70% of total transactions in the department) – however, the transactions conducted by the top 20% heavy buyers by value in the *Men's clothing* department only represented 36% of the total transactions, despite their revenue contribution of 68%. Service initiatives or activation programs that are tied with the frequency of transactions may work well to boost revenue in food, department, but not in *Men's clothing*. This approach of looking into Pareto share within each department can also be applied to businesses having a portfolio of brands or products. There may be varying degree of Pareto share and their contribution stability over time if each brand or product has intrinsic differences on their value and purchase frequency.

Finally, understanding the (in)stability of heavy buyers for the store as a whole and across departments will help retailers more effectively allocate resources to customer retention versus acquisition. Whilst retention strategies to ensure that heavy buyers will return to the department store for their future product needs is important, the study has also highlighted the parallel between brand growth and the revenue contribution from each department to the whole store. Continuous shopper acquisition is important for growth. Further, rather than fixating at the heavy buyer stability across the total business, the knowledge at each component within the business (e.g., departments, brands, or products) would enable more effective strategies. Within the department store context, more precise benchmarks will also allow retailers to assess the impact of heavy buyer retention initiatives more effectively, which will improve marketing effectiveness over time. By identifying low heavy buyer stability departments, it could be possible to avoid pitfalls from heavy buyer targeting in those departments. For departments with high stability such as *Food* or *Beauty products*, targeting heavy buyers for promotions and offers is likely to capture continuing heavy buyers. However, for lower heavy buyer stability levels, such as *Kids & Baby* or *Sports*, targeting solely heavy buyers based on last year's purchasing would miss reaching past light buyers who can potentially turn into heavy buyers in the next period.

Limitations and Future Research

This study was conducted on one department store chain in East Asia. There was no accompanying information or data on the adherence to loyalty card use as a portion of the total number of transactions, due to the condition of the data sharing. Accordingly, there were likely to be transactions outside of those recorded here (i.e., shoppers who opted not to scan their loyalty card or those who did not join the loyalty program). Further research should look at alternative data sources with more comprehensive transaction coverage. The generalisability of the findings can be further explored through data from various countries, age of the business, and different types of department store chains (e.g., discount outlets like TJ Maxx versus mainstream department stores such as Macy's or Bloomingdales), as well various customer cohorts based on how long they have shopped at the retailers. The research can also be further improved through the inclusion of other demographic variables, such as household size and income, as well as changes in geographic location which may provide further context into varying stability rates across different departments and over time.

Future research should explore if there is a difference in the effectiveness of marketing activities directed at departments with low heavy buyer stability compared to those with high heavy buyer stability. Low stability may indicate more opportunity, but high stability might mean more predictable results. Along with further exploration of heavy buyer stability, future research can also delve deeper into how closely department purchases follow the known Double Jeopardy line and whether systematic deviations can be observed among departments with similar characteristics (e.g., *Beauty products*).

The approach to creating benchmarks and evaluating promotional activity on heavy buyers also provides a new approach for future research on the dynamics of sales and promotion activities in department stores and how they attract heavy vs. light buyers in each department. Future testing should involve a more comprehensive range of marketing activities across different departments.

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Table 1 - Pareto Share in Previous Studies

Study	Year	Analysis Period	Unit of analysis	Scope	Countries	Average Top 20% Contribution
CPG categories						
Schmittlein, et al.	1993	1 year	Transactions	4 CPG categories	US	52%
Jarvis et al.	2003	1 year	Transactions	4 wine sub-categories	AU	64%
Sharp and Romaniuk	2007	1 year	Transactions	CPG categories	US, AU, ZA	52%
Romaniuk and Wight	2015	1 year	Transactions	12 CPG categories	UK	61%
Romaniuk and Sharp	2016	1 year	Transactions	9 CPG categories	BR, CN, ID, IN, KE, MX, MY, NG, PH, TR	53%
Graham, et al.	2017	1 year	Transactions	22 CPG categories from supermarket loyalty card	UK	50%
Anesbury, et al.	2020	1 year	Transactions	5 Fresh fruit and vegetable categories	US	61%
Kim, et al.	2017	6 years	Sales value	22 CPG categories	US	73%
Graham, et al.	2017	5 years	Transactions	22 CPG categories from supermarket loyalty card	UK	60%
Unweighted Average (All CPG studies)						**58%**
Other categories						
Litvin	2000	1 year	Transactions	Vacation Travel	SG	40%
Brynjolfsson, et al.	2011	1 month	Transactions	Women's clothing – online or catalog.	US	57% *(catalog)* 53% *(online)*
Bennett	2016	10 years	Transactions	Airplane purchases	Global	56%
McCarthy and Winer	2019	2 years	Transactions	Product and service companies	US	67%
Martin, et al.	2020	1 year	Transactions	10 types of retailers	US	50%
Martin, et al.	2020	1 year	Value	10 types of retailers	US	38%
Unweighted average (All non-CPG studies)						**52%**

Table 2 – Department Size in Penetration, Average Purchase Frequency and Value

Department	Department revenue contribution to the total amount	% Shoppers bought at least once in the year	Transaction /Annum	
			Frequency	Avg. Value (USD)
Total store	**100**	**100**	**44.8**	28.99
Food items	31.6	75.9	36.1	8.10
Women's clothing	30.5	54.6	4.8	72.44
Décor and furniture	10.5	35.5	3.3	50.63
In-store dining	2.4	26.6	3.6	13.67
Beauty products	12.2	26.4	6.2	45.26
Men's clothing	5.2	19.8	2.1	46.73
Kids & Baby products	2.5	13.5	2.8	33.12
Sports products	3.2	9.6	1.7	90.42
Books	0.1	2.4	2.1	10.11
Gifts	0.7	2.0	1.0	126.35
Traditional costume	0.8	1.4	1.2	192.06
Cleaning products	0.2	1.2	2.4	33.72
Massage products	0.1	1.0	1.8	27.39

Table 3 – Contributions of Top 20% Shoppers and Stability % Over Time

Department	Top 20% of Shoppers by Value		Heavy Buyer Stability %		Top 20% of Shoppers by Transactions		Heavy Buyer Stability %	
	Value % of Total	Trx % of Total	Yr 1 → 2	Yr 1 → 3	Value % of Total	Trx % of Total	Yr 1 → 2	Yr 1 → 3
Total store	**71**	**60**	**69**	**64**	**56**	**72**	**76**	**69**
Traditional costume	86	43	22	17	64	62	22	16
Décor and Furniture	80	47	39	33	46	61	49	41
Gifts	78	44	11	8	65	52	13	9
Women's clothing	70	51	54	48	58	62	59	54
Beauty products	70	59	72	62	66	62	70	59
Massage products	70	54	42	32	62	62	44	33
Food items	69	70	74	67	60	77	75	68
Men's clothing	68	36	40	34	53	67	46	37
Kids & Baby	68	52	34	25	58	61	40	33
Books	67	59	38	31	57	61	40	32
In-store dining	66	60	55	48	61	65	57	48
Sports products	65	53	39	32	58	57	40	32
Cleaning products	65	52	63	56	53	61	65	55
Average	***71***	***52***	***45***	***38***	***58***	***62***	***48***	***40***

Table 4 – Buyer Sharing Across *Heavy Buyers*: Three-year Average

Department	Pen.* %	A	B	C	D	E	F	G	H	I	J	K	L	M
A – Food items	15.3		*24*	20	17	12	9	5	4	2	1	1	1	1
B – Women's clothing	10.9	34		24	16	19	10	7	7	1	1	1	1	1
C – Décor and Furniture	7.1	43	36		18	16	13	8	7	2	1	1	1	1
D – In-store dining	5.3	49	32	24		15	10	9	6	2	1	1	1	1
E – Beauty products	5.3	35	39	22	15		8	6	7	1	1	1	1	1
F – Men's clothing	4.0	33	26	23	13	10		5	7	1	1	1	1	0
G – Kids & Baby prdcts.	2.7	*31*	30	20	17	13	8		6	2	1	1	1	1
H – Sports products	1.9	*32*	42	25	15	19	14	8		1	1	1	1	1
I - Books	0.5	**53**	31	29	27	16	13	12	5		1	1	2	2
J - Gifts	0.4	44	*20*	22	10	8	8	5	3	1		1	0	0
K - Traditional costume	0.3	41	41	30	17	15	11	7	6	2	1		1	1
L - Cleaning products	0.2	**65**	**45**	**35**	**30**	**30**	14	7	9	4	1	1		2
M- Massage products	0.2	43	39	33	20	20	9	8	10	4	1	1	2	
Average Duplication		**42**	**34**	**24**	**17**	**16**	**10**	**7**	**7**	**2**	**1**	**1**	**1**	**1**

*** Note:** *Penetration figures are calculated based on the number of heavy customers in the department as a proportion of the total number of customers enrolled in the loyalty program, to ensure comparable figures across departments. Co-occurrence levels above 10pp deviation are shown in bold.*